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Drought in the Southeastern USA: an assessment of downscaled CMIP5 models

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ABSTRACT: The Southeastern USA has been repeatedly affected by severe droughts that have impacted the environment and economy of the region. In this study, the ability of 32 downscaled Coupled Model Intercomparison Project Phase 5 (CMIP5) models, downscaled using localized constructed analogs (LOCA), to simulate historical observations of dry spells from 1950 to 2005 are assessed using Perkins skill scores and significance tests. The analysis is split between cold and warm seasons based on timing of agricultural planting and harvesting dates of key crops. The models generally simulate the distribution of dry days well but there are significant differences between the ability of the best- and worst-performing models, particularly when it comes to the upper tail of the distribution. Only the top models provide a good estimate of extreme dry-spell lengths with simulations of 20 yr return values within ±5 d of observed values across the region. The findings provide guidance on selection of a suitable model ensemble for assessment of future drought risk in the Southeastern USA.

KEY WORDS: Drought · Localized constructed analogs · LOCA climate models · Precipitation · Southeastern USA

1. INTRODUCTION

In this study, historical droughts in the Southeastern USA (hereafter, 'the Southeast') are evaluated using 32 downscaled climate models. The Southeast has been subject to increased population pressure following rapid development, which has resulted in multiple water-related conflicts. The conflicts are foremost related to water quantity and allocation and include, but are not limited to, the 'tri-state water dispute' (Alabama, Georgia and Florida), water supply problems in the Tampa Bay region (Florida) and groundwater pumping around Memphis (Tennessee) leading to decreased surface discharge in Mississippi (Yuhas & Daniels 2006, Manuel 2008, Upholt 2015). Due to their complexity, these conflicts typically persist over multiple years, and tend to flare up at times of drought. Florida and Mississippi are also among the 14 states identified by the Natural Resources Defense Council (2010) as being projected to face high to extreme water supply shortages by 2050, due to increased population in combination with climate change.

Even though the Southeast has abundant vegetation and is mostly in a humid subtropical climate, the region is no stranger to droughts. Recent extended periods of dry conditions include the years of 1986–1988, 1998–2002 and 2006–2009 (Seager et al. 2009, Pederson et al. 2012, Kunkel et al. 2013). Following above-normal temperatures and low precipitation rates, 2016 also turned out to be an abnormally dry year, with parts of the Southeast being in extreme or exceptional drought. During the fall of 2016, historical records of most consecutive days without rainfall were broken throughout the continental parts of the Southeast, leading to extensive agricultural losses and sparking widespread wildfires throughout the region (Gattis 2016, National Drought Mitigation Center 2017a, NOAA National Centers for Environmental Information 2017a). The spring of

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2017 brought relief to most of the Southeast, apart from Florida where Governor Rick Scott declared a 'state of emergency' in April 2017 due to the dry conditions that were expected to continue throughout the spring (Scott 2017). By the end of May, over 50% of the state was in severe to extreme drought (National Drought Mitigation Center 2017b), sparking extensive wildfires that caused road closures due to smoke, and caused agricultural losses, following the lack of precipitation (NOAA National Centers for Environmental Information 2017b).

However, these droughts cannot be attributed to recent climate change alone. The 1930s experienced very dry conditions and above-normal temperatures, and the droughts the Southeast has faced in the past century do not stand out as extreme in the multi-century historical record. In fact, for much of the region, the last century has been slightly wetter than previous historical records indicate (Seager et al. 2009, Pederson et al. 2012, Kunkel et al. 2013). Focusing on the second half of the 20th century, Powell & Keim (2015) found no spatial trends in droughts in the Southeast, but suggested that wet spells have become shorter. This is further confirmed in findings by Martinez et al. (2012) and Irizarry-Ortiz et al. (2013) in their studies of the climatology of Florida. Inter- to intra-annual modes of climate variability have been attributed to several large-scale atmospheric drivers, including, but not limited to, the Atlantic Multidecadal Oscillation, El Niño-Southern Oscillation, North Atlantic Oscillation and Pacific–North American pattern, which have been identified as potential drivers of hydroclimatic variability and drought in the Southeast (Ropelewski & Halpert 1987, Dracup & Kahya 1994, Enfield et al. 2001, Ortegren et al. 2011, Labosier & Quiring 2013, Engström & Waylen 2017).

Recognizing the challenges associated with the re-occurring droughts in the Southeast, this study aims to analyze how well the downscaled models replicate historical dry spells of consecutive days without precipitation. Through identification of models best able to replicate the probability density function of consecutive dry days and specifically match the observed long-lasting or extreme dry spells (above the 90th percentile), the best-performing models can be used to shed light on what severity of droughts the region may be facing in the future. Identifying the best-performing models based on historical observations gives a higher level of confidence in future projections, compared with including an ensemble-approach utilizing all models, both well and poor performing, in future simulations (Perkins 2011).

Previous studies have examined the performance of multimodel ensembles of Coupled Model Intercomparison Project Phase 5 (CMIP5) models over North America and found that the ability of models to simulate surface climatology is highly variable between models and across regions (Sheffield et al. 2013). Model biases are more pronounced in representation of extreme values of temperature and precipitation. Daily maximum temperature is represented well in some models in the southern USA, but precipitation is not simulated well in the Southeast, with slightly low model biases likely related to large-scale circulation patterns and underestimation of tropical cyclone numbers (Sheffield et al. 2013). However, CMIP5 models have been found to replicate spatial patterns and magnitudes of consecutive dry days well, as consecutive dry days are usually present at a larger spatial scale than extreme precipitation events, which are more localized and difficult for models to resolve (Sillmann et al. 2013).

Although there have been previous studies evaluating the performance of climate models in replicating high temperatures (Keellings 2016), cool temperatures (Pan et al. 2013) and extratropical storms (Colle et al. 2013), in the Southeast, Perkins (2011) noted that the climate model skill varies depending on what parameter is analyzed. It should be emphasized that model evaluation is dependent on the metrics utilized and on the variable being reproduced. A full and robust assessment of model performance should include all variables and incorporate the potential influence of large-scale atmospheric drivers and temporal variability (Brekke et al. 2008, Hidalgo & Alfaro 2015). This type of assessment is not the objective of this study, which focuses on the skill of models in reproducing certain aspects of extreme dry events. The assessment of skill is based on comparison of simulations of the entire statistical distribution of consecutive dry days. A temporal analysis, identifying specific dry spells, is not the focus of this paper study. However, if model skill is high, it can be assumed that the model simulates the distribution of consecutive dry day lengths, and therefore, also the drivers responsible for their occurrence.

Downscaled climate models generally perform poorly in simulation of precipitation, particularly when it comes to extremes. The simulations are often either lacking in variance through producing too many drizzle days (brought about by averaging), and/or lacking in spatial detail through introduction of high levels of spatial autocorrelation (Hidalgo et al. 2008, Maraun 2013, Hwang & Graham 2014). In this study, we examine the performance of a new downscaled dataset in simulation of lengths of dry periods across the Southeast from 1950 to 2005. This new dataset has been constructed using a new downscaling technique, localized constructed analogs (LOCA) (Pierce et al. 2014), that should be able to produce better estimates of extreme precipitation.

2. MATERIALS AND METHODS

2.1. Data

Thirty-two downscaled global climate models (GCMs) from the World Climate Research Programme's (WCRP) CMIP5 (Table 1) were downloaded from the Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections archive (http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/dcpInterface.html). These daily data are downscaled to a spatial resolution of 1/16° for the period 1950–2005 using LOCA, which, unlike other constructed analog techniques, constructs the downscaled field point-by-point from a single best match analog day rather than using a weighted sum of numerous analog days (Pierce et al. 2014). By reducing the averaging normally found in other constructed analog methods and by using a point-by-point approach, LOCA generally produces better estimates of extremes, reduces the tendency to produce drizzle through averaging of low and high values, and generates more realistic spatial autocorrelation (Pierce et al. 2014). One LOCA

Table 1. List of Coupled Model Intercomparison Project Phase 5 (CMIP5) models evaluated

Model name	Affiliation
ACCESS1-0	CSIRO (Commonwealth Scientific and Industrial Research Organisation, Australia) and BOM (Bureau of Meteorology, Australia)
ACCESS1-3	
BCC-CSM1-1	Beijing Climate Center, China Meteorological Administration
BCC-CSM1-1-m	
CanESM2	Canadian Centre for Climate Modeling and Analysis
CCSM4	National Center for Atmospheric Research
CESM1-BGC	National Science Foundation, Department of Energy, National Center for Atmospheric Research
CESM1-CAM5	
CMCC-CM	Centro Euro-Mediterraneo per I Cambiamenti Climatici
CMCC-CMS	
CNRM-CM5	Centre National de Recherches Météorologiques/Centre Européen de Recherche et Formation Avancée en Calcul Scientifique
CSIRO-Mk3-6-0	Commonwealth Scientific and Industrial Research Organization, Queensland Climate Change Centre of Excellence
EC-EARTH	EC-EARTH consortium
FGOALS-g2	LASG, Institute of Atmospheric Physics, Chinese Academy of Sciences; and CESS, Tsinghua University
GFDL-CM3	NOAA Geophysical Fluid Dynamics Laboratory
GFDL-ESM2G	
GFDL-ESM2M	
GISS-E2-H	NASA Goddard Institute for Space Studies
GISS-E2-R	
HadGEM2-AO	Met Office Hadley Centre (additional HadGEM2-ES realizations contributed by Instituto Nacional de Pesquisas Espaciais)
HadGEM2-CC	
HadGEM2-ES	
inmcm4	Institute for Numerical Mathematics
IPSL-CM5A-LR	Institut Pierre-Simon Laplace
IPSL-CM5A-MR	
MIROC-ESM	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo) and National Institute for Environmental Studies
MIROC-ESM-CHEM	
MIROC5	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies and Japan Agency for Marine-Earth Science and Technology
MPI-ESM-LR	Max Planck Institute for Meteorology
MPI-ESM-MR	
MRI-CGCM3	Meteorological Research Institute
NorESM1-M	Norwegian Climate Centre

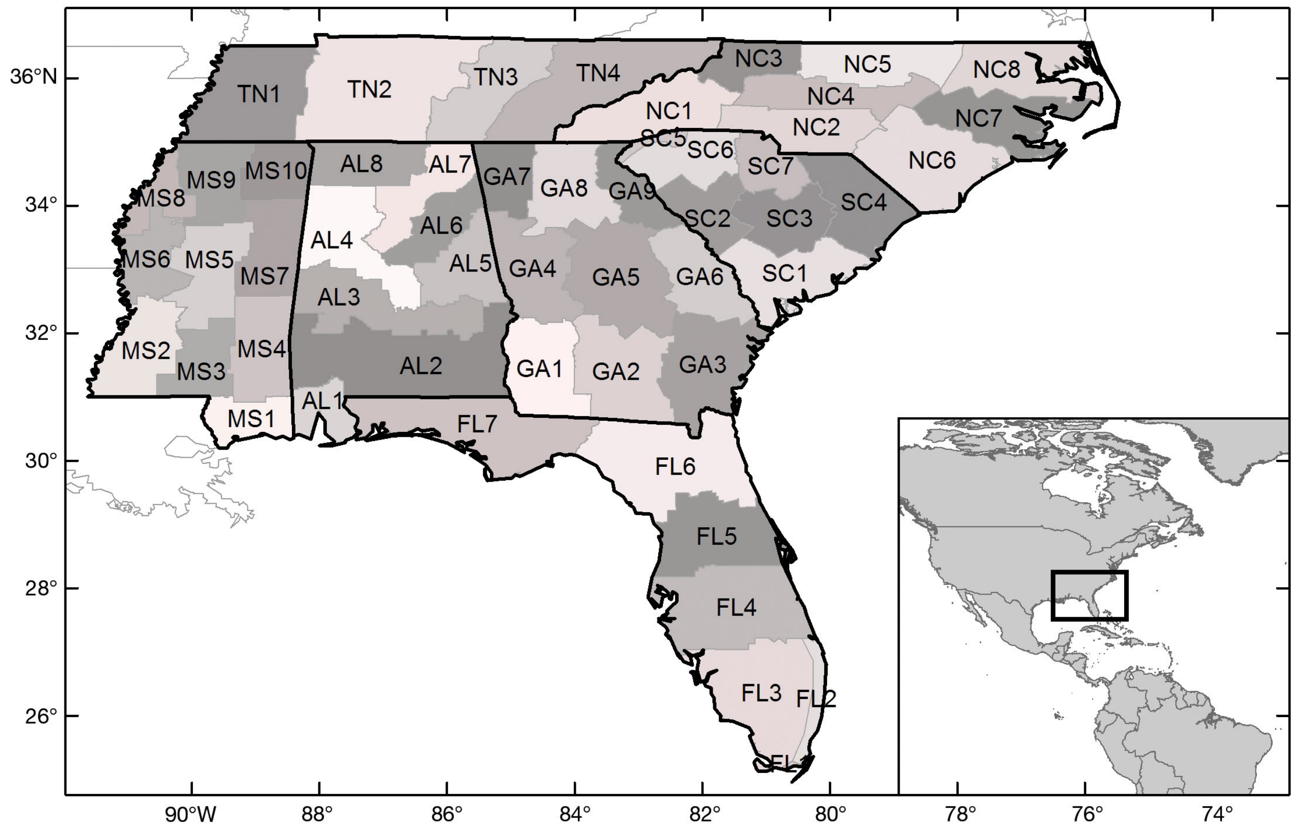

Fig. 1. Southeastern USA study region with climate divisions. The climate divisions are named based on state abbreviation (Florida: FL; Georgia: GA; South Carolina: SC; North Carolina: NC; Tennessee: TN; Mississippi: MS; Alabama: AL) followed by number

ensemble member is available for each of the 32 models in the archive.

The precipitation dataset used to evaluate the CMIP5 LOCA models is model-derived from observed data developed for the North American Land Data Assimilation System Variable Infiltration Capacity simulations over North America (www.colorado.edu/lab/livneh/data) (Maurer et al. 2002, Livneh et al. 2015). These daily data have a spatial resolution of 1/16° for the period 1950–2005. The dataset is compiled from over 20 000 National Oceanic and Atmospheric Administration (NOAA) Cooperative Observer Network (COOP) stations, gridded using a synergraphic mapping system (SYMAP) algorithm (Shepard 1984, Widmann & Bretherton 2000), and then interpolated using an asymmetric spline (Maurer et al. 2002).

The USA can be divided into numerous climate regions and what comprises the Southeast is not set in stone, but varies with the scope of the analysis (Ortegren et al. 2011, Kunkel et al. 2013, Keellings 2016, Engström & Waylen 2018). In this study, the Southeast is defined as the southern states east of the Mississippi river, and includes Alabama, Florida, Georgia, Mississippi, North Carolina, South Carolina and Tennessee (Fig. 1). The results are presented by climate division (nClimDiv, provided by NOAA) to reduce noise and give a more generalized picture of the performance of the climate models. Due to generally high evapotranspiration rates in this geographical region, a dry day is defined according to the definition of no measureable precipitation as a day with less than 3 mm of precipitation (Wilks 2011, Kunkel et al. 2013).

The data are divided into 2 seasons, recognizing that lack of precipitation during the warm (growing) season will lead to excessive economical and environmental implications, compared with the cold season. The warm season is defined as April–October, while the cold season constitutes the months of November–March. The seasons are generalized and based on the US Department of Agriculture's data on planting and harvesting dates of field crops in the states of interest (US Department of Agriculture National Agricultural Statistics Service 2010).

2.2. Model evaluation

The performance of the LOCA downscaled CMIP5 models are evaluated using distribution-based and extreme-based (upper tail) Perkins skill scores (Perkins et al. 2013), as the focus of this study is on long-lasting droughts that can severely affect the environment and economy of the Southeast. These skill scores compare the distribution of counts of consecutive dry days between observed and modeled data in each grid cell for the entire period (1950–2005). Significance tests of these skill scores are made following the method of Keellings (2016) using inverse mapping of the cumulative distribution function of the observations and random number generation.

A probability density function (PDF)-based skill score (Perkins et al. 2007) is calculated by taking the cumulative minimum value of the observed and modeled distributions of periods of consecutive dry days (Eq. 1). If the 2 PDFs completely overlap, the skill score will equal one.

$$\mathrm{PDF}_{\mathrm{score}} = \sum_{1}^{n} \min(Z_{\mathrm{m}}, Z_{\mathrm{o}}) \quad (1)$$

where n is the number of intervals at which the PDF has density, Z_m is the density of values at a given interval from the model and Z_o is the density of values at a given interval from the observations. The intervals are generated from the minimum observed or modeled (whichever is lower) length of consecutive dry days to the maximum observed or modeled (whichever is higher) length of consecutive dry days in 1 d increments.

A tail skill score for extreme lengths of consecutive dry days is calculated in the same manner as above, by taking the cumulative minimum value of 2 PDFs, but only the overlap above the 90th percentile of the observation PDF is examined to focus on extreme lengths of consecutive dry days.

Interpretation of skill scores is somewhat subjective, e.g. the closer to 1 the better, and it is unclear what threshold constitutes a good score. Therefore, to give a more probabilistic assessment of skill scores, a skill score significance test developed by Keellings (2016) is employed. The Keellings skill score significance test uses a Monte Carlo and inverse mapping approach to construct random cumulative distribution functions that are constrained to be of the same distribution as the observations. The constructed densities and observation densities are compared using the PDF skill score and this process is repeated 1000 times to derive an empirical distribution of constructed skill scores. The model skill score is considered to be significantly lower than could be expected at random if it falls below the 5th percentile of all constructed skill scores. If the model skill score fails this test, it is lower than at least 95% of the constructed skill scores and indicative of a model PDF that is significantly different from the observation PDF. Using the PDF and tail skill scores, each model was ranked from highest to lowest based on average performance across all climate divisions. From this ranking, the top 5 best-performing and bottom 5 worst-performing models are identified in each season.

The generalized extreme value (GEV) distribution is used to assess differences in lengths of dry spells between observations and models. The GEV is commonly applied to extreme hydrometeorological variables (Zwiers & Kharin 1998, Kharin et al. 2005, Waylen et al. 2012). The GEV is chosen as it makes no *a priori* assumptions regarding the form of the extreme value distribution (Jenkinson 1955). Here we estimate the GEV parameters with the method of maximum likelihood using the extRemes package in R. The cumulative distribution function of the GEV is given by:

$$P(x) = \exp - \left\{1 + \xi \frac{x - \mu}{\sigma}\right\}^{-1/\xi} \quad (2)$$

where μ is the location parameter (central tendency), σ is the scale parameter (variance) and ξ is the shape parameter (skew) (Coles 2001). Return periods are estimated using the fitted GEV for an ensemble of the best- or worst-performing models, as identified by the skill score measures, and compared with the observations.

3. RESULTS

Before evaluating the downscaled models, a Mann–Kendall trend test (Kendall 1955) was used to assess the presence of a statistically significant (0.05 significance level) trend in the observed time series of dry spells in each grid cell. Few cells exhibit a significant trend in dry spells and, in total, there is no field significance. Model PDF skill scores by climate divisions are shown in heat maps for the warm season (Fig. 2) and cold season (Fig. 3). Model tail skill scores are shown for the warm season (Fig. 4) and cold season (Fig. 5). Model PDF skill score significance by climate divisions are also shown in heat maps for the warm season (Fig. 6) and cold season (Fig. 7). The tail skill score significances are not shown, as the tail skill scores are not significant

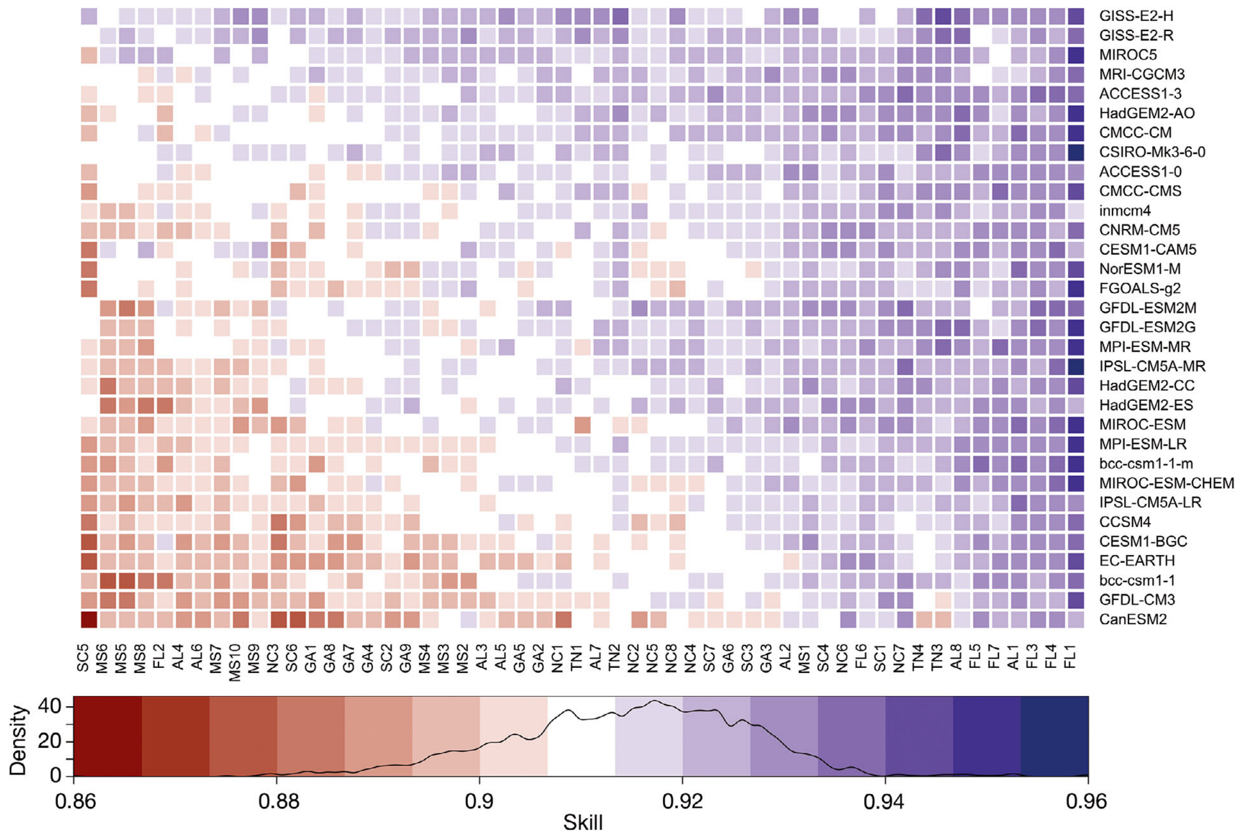

Fig. 2. Heat map of warm season probability density function (PDF) skill score for each downscaled model by climate division. Bottom plot shows density of skill scores in the above heat map. Values closer to 1 indicate better overlap between observed and modeled distribution of dry spells

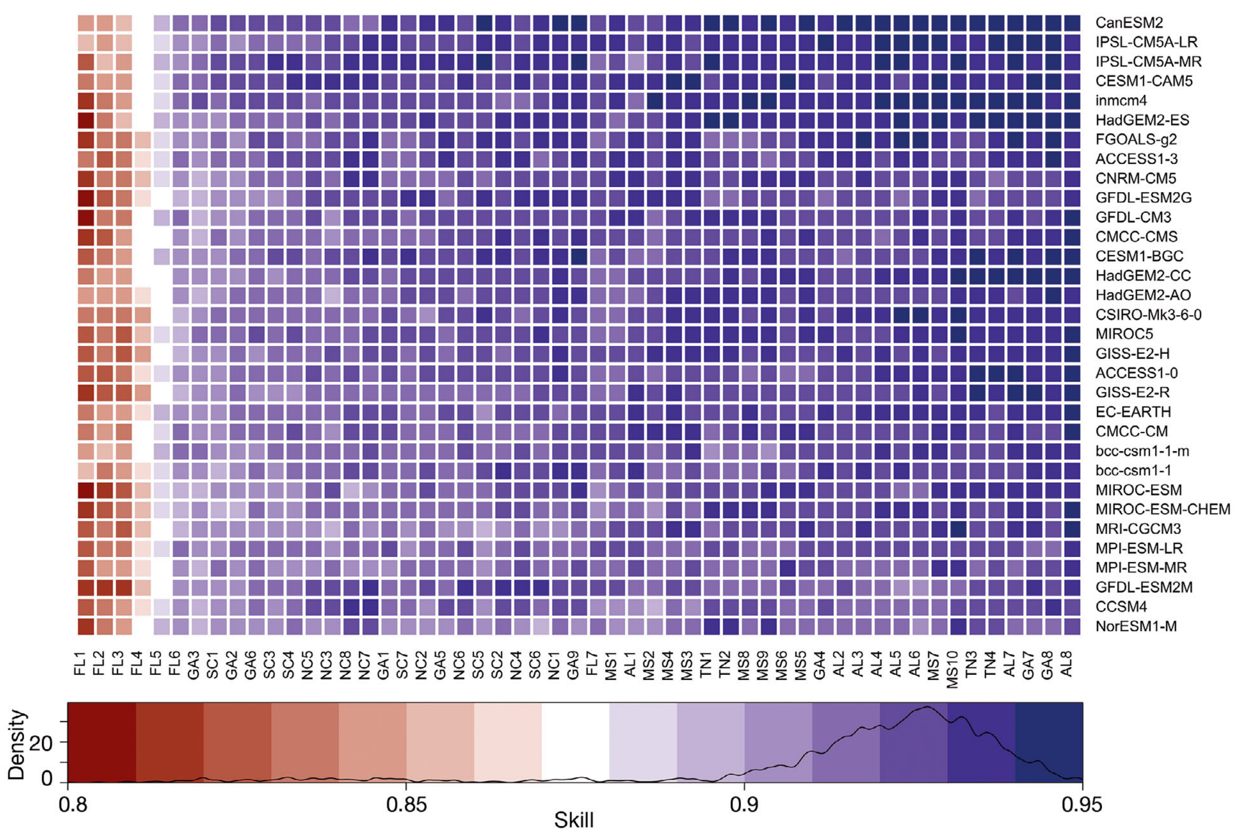

Fig. 3. As Fig. 2 for cold season probability density function (PDF)

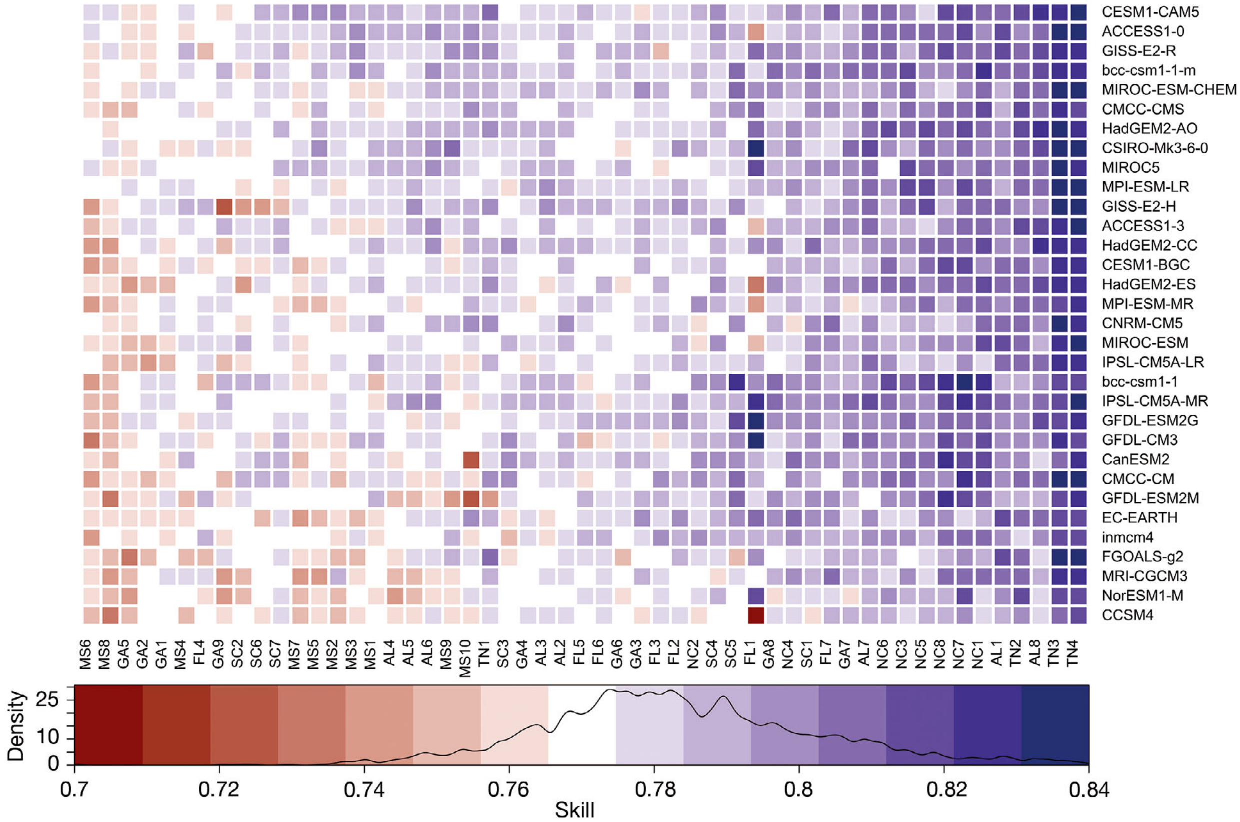

Fig. 4. As Fig. 2 for warm season tail skill score

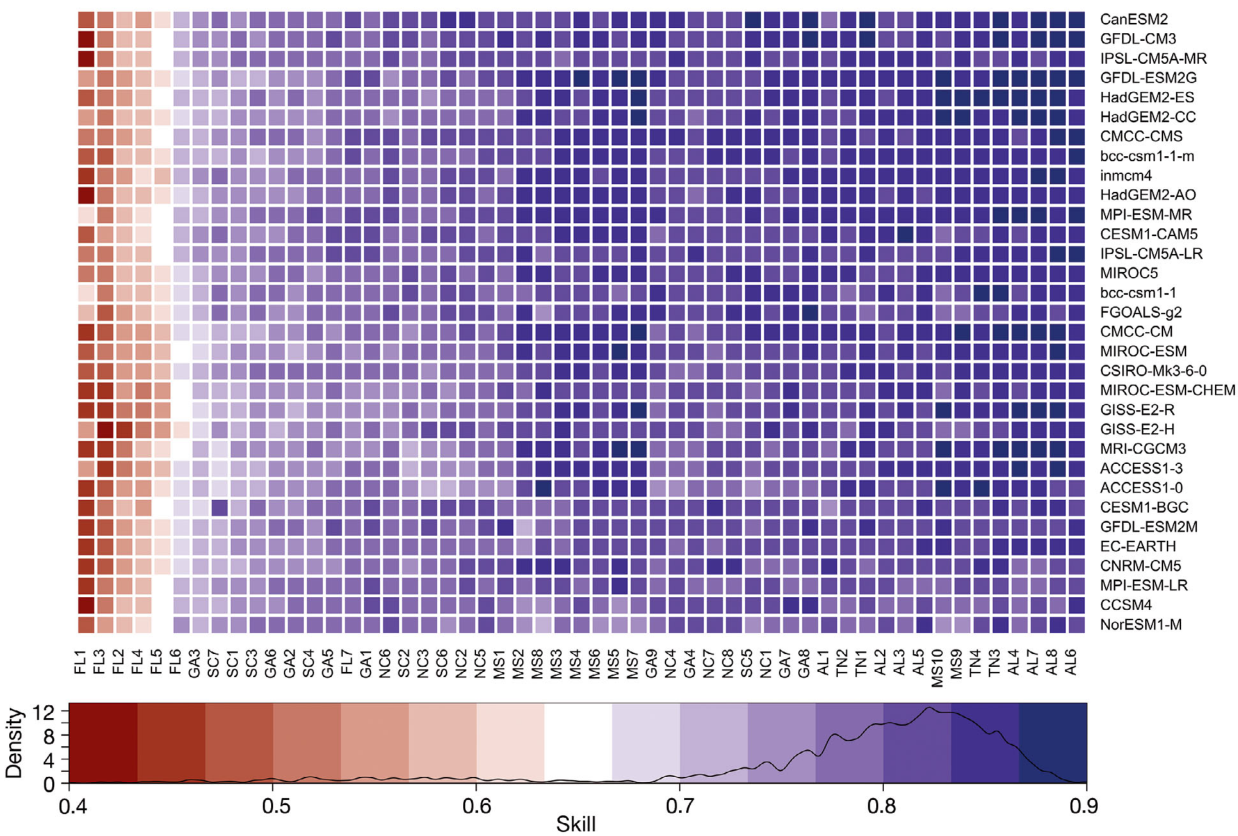

Fig. 5. As Fig. 2 for cold season tail skill score

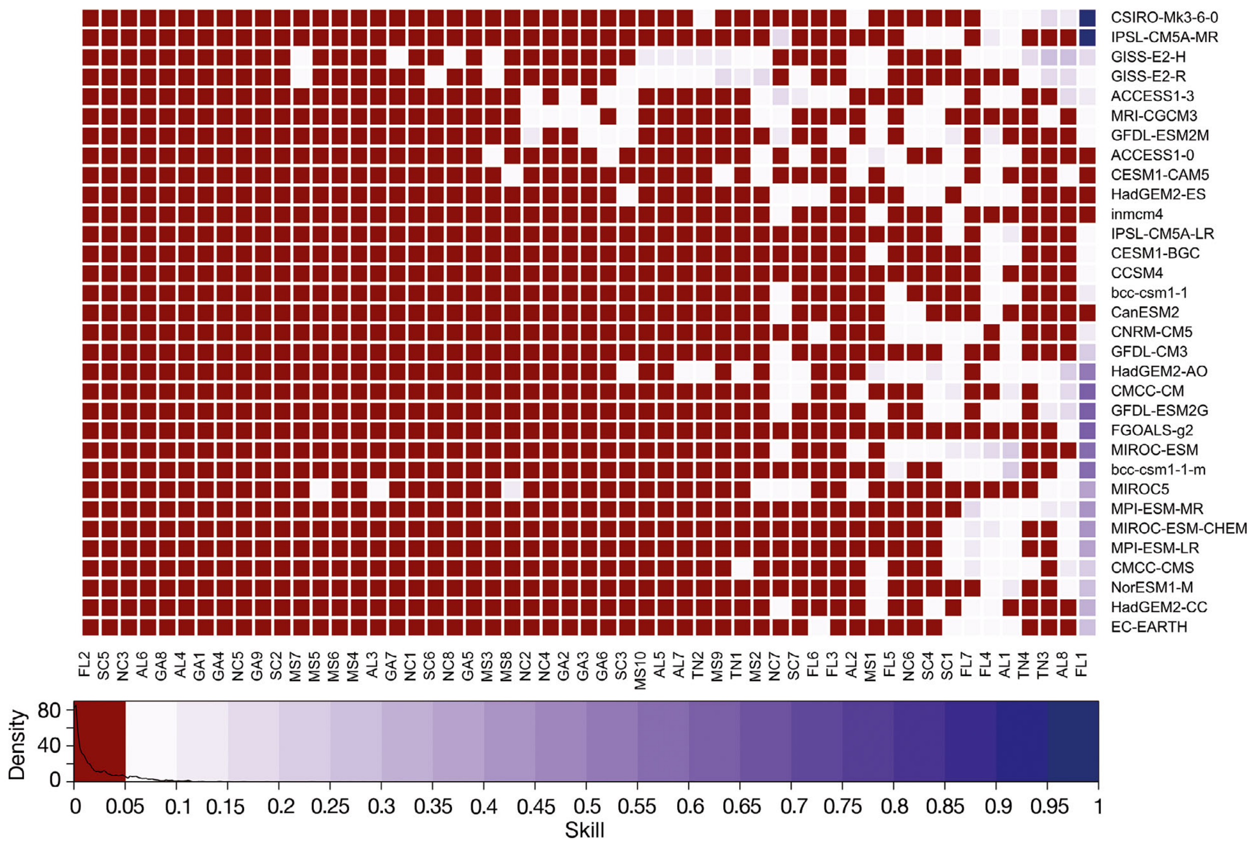

Fig. 6. Heat map of warm season probability density function (PDF) skill score significance for each downscaled model by climate division. Bottom plot shows density of skill score significance in the above heat map. Significance scores below 0.05 indicate a PDF skill score that is significantly lower than could be expected at random, and suggests a poor fit between model and observation

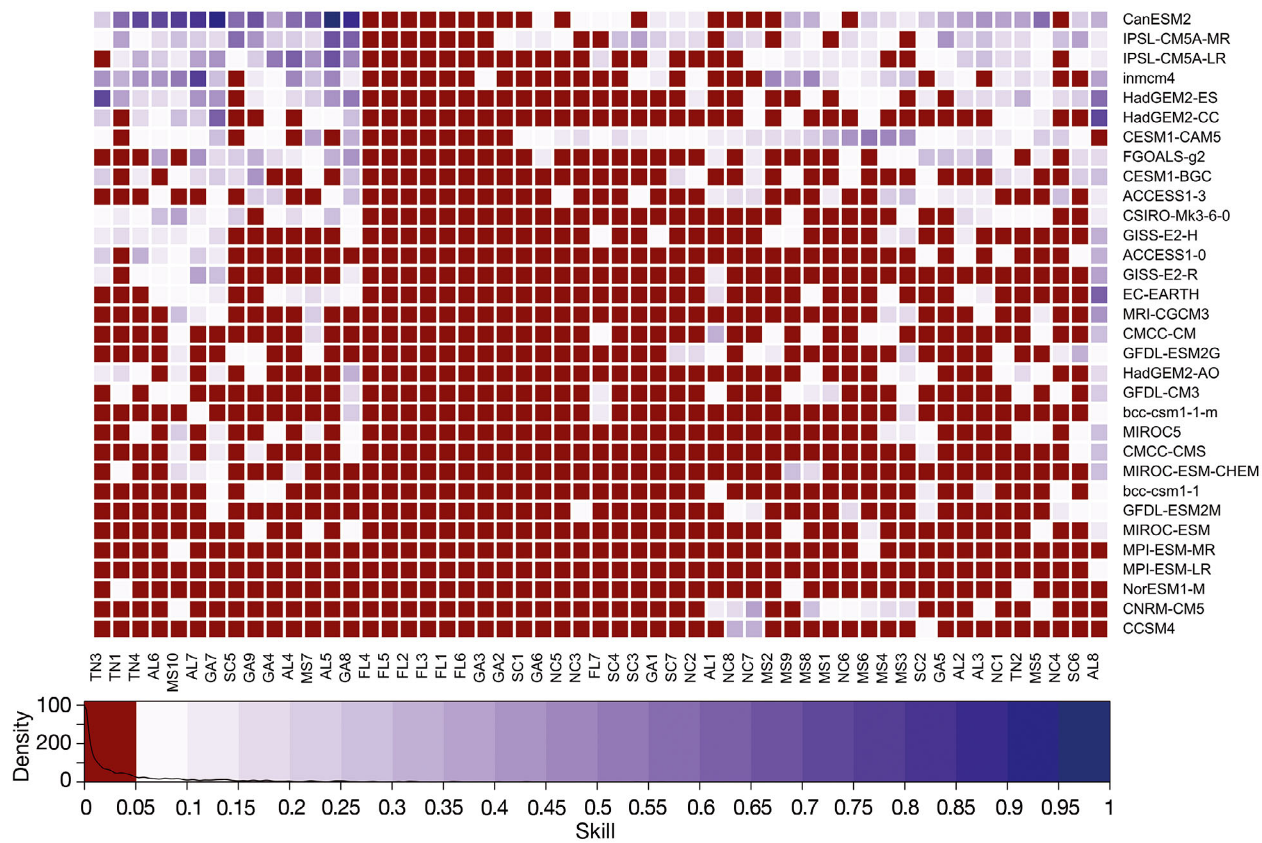

Fig. 7. As Fig. 6 for cold season probability density function (PDF) skill score significance

across all models, climate divisions and seasons. The top 5 best-performing models identified using the PDF skill scores are shown in Fig. 8a–e for the warm season and Fig. 8f–j for the cold season. The cold season shows continental clusters of climate divisions where the models' performance is significant, while the warm season show more geographically dispersed significance. The models have the greatest difficulty in simulating dry spells in south Florida during the cold season. Only PDF skill scores were used to identify the best- and worst-performing models as the tail skill scores were not significant.

To further investigate the models' ability to replicate longer dry spells, the length of dry spell that constitutes the 20 yr return period was identified. For the warm season, such a drought lasts 33–49 d, with the shortest droughts found in the central and northwestern part of the region (Fig. 9a). During the cold

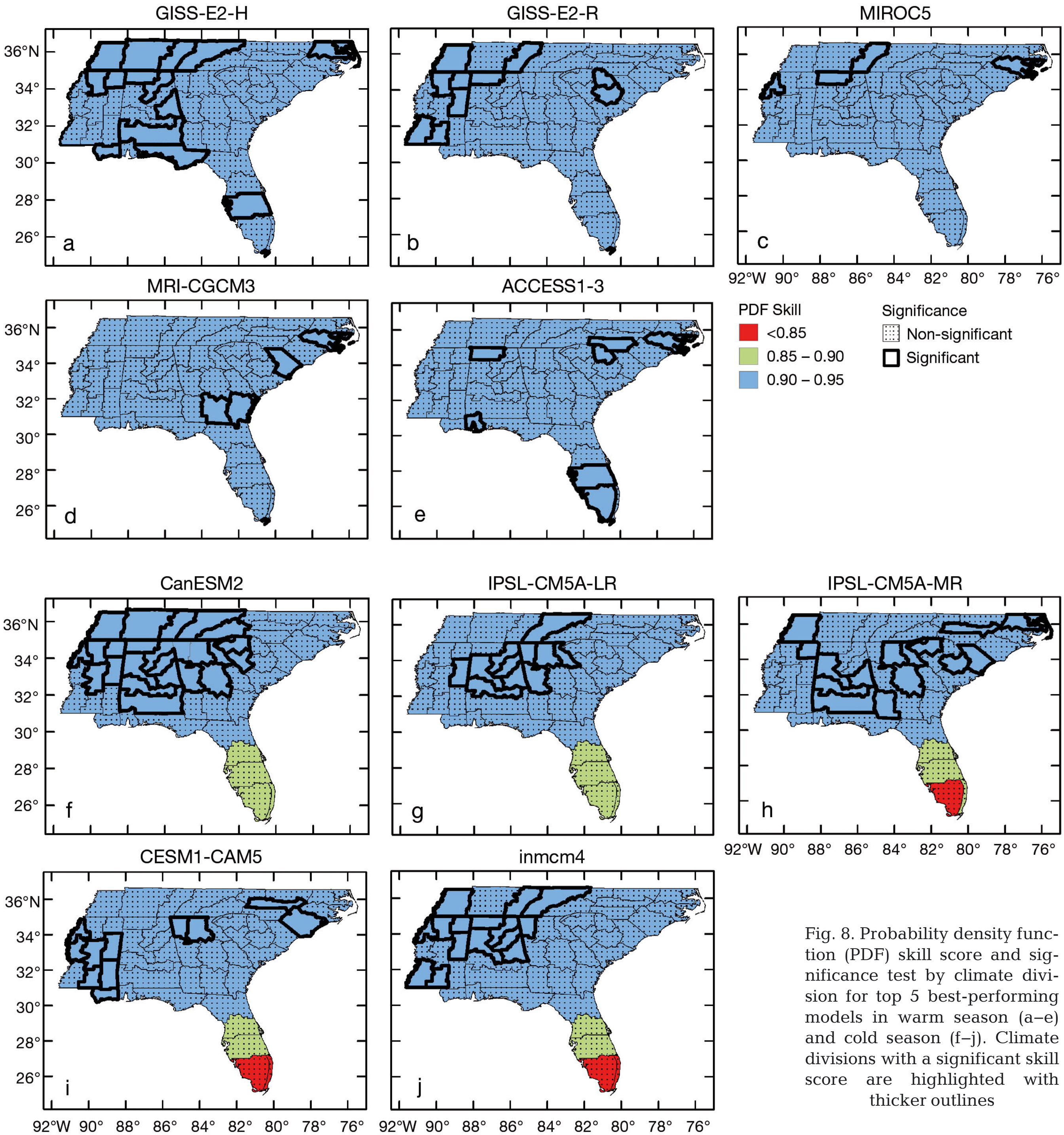

Fig. 8. Probability density function (PDF) skill score and significance test by climate division for top 5 best-performing models in warm season (a–e) and cold season (f–j). Climate divisions with a significant skill score are highlighted with thicker outlines

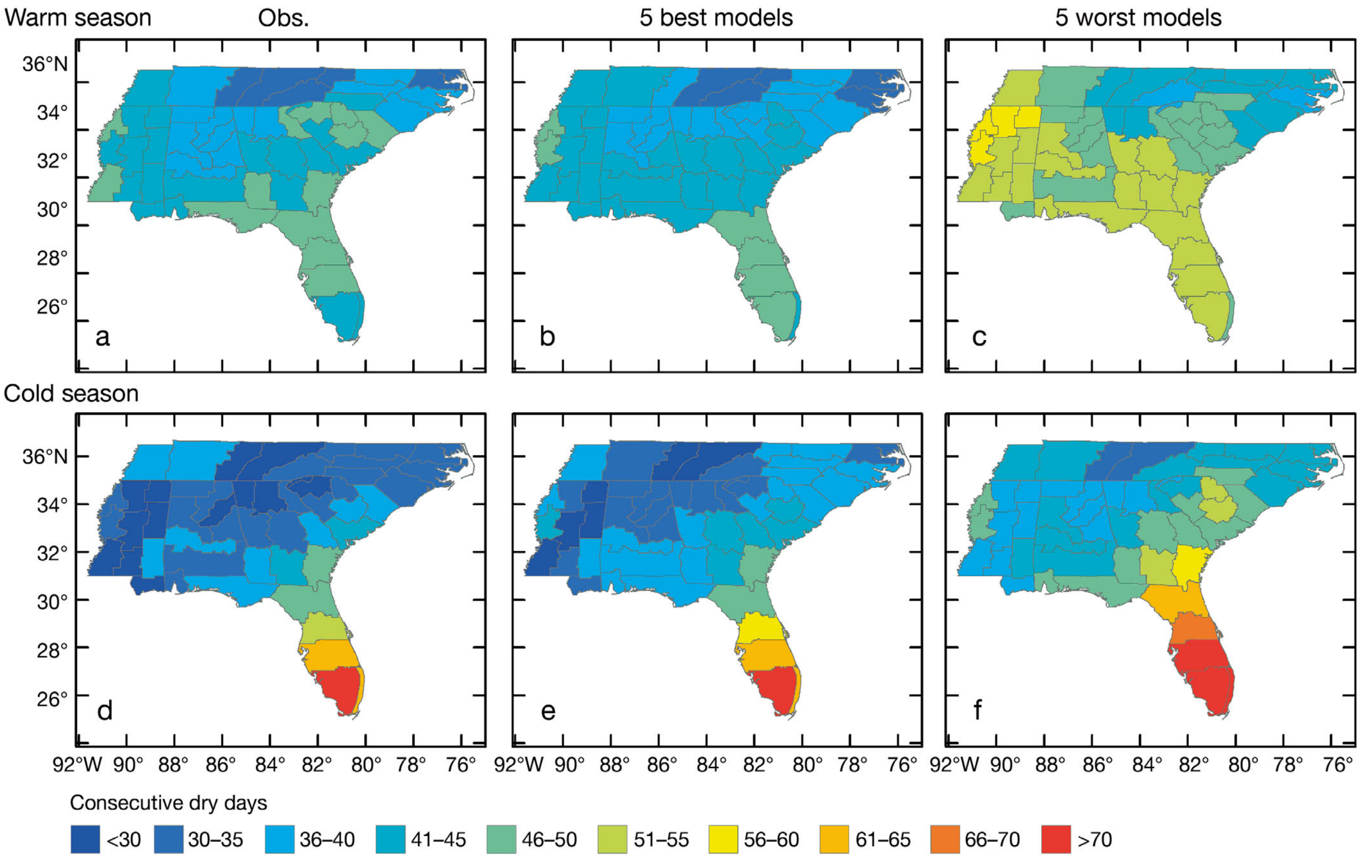

Fig. 9. The 20 yr return values of consecutive dry days for: (a) warm season observations; (b) ensemble of 5 best models based on probability density function (PDF) skill for warm season; (c) ensemble of 5 worst models based on PDF skill for warm season; (d) cold season observations; (e) ensemble of 5 best models based on PDF skill for cold season; (f) ensemble of 5 worst models based on PDF skill for cold season

season, droughts with a 20 yr return period become more extreme lasting up to 77 d in southeastern Florida, while the more continental parts of the study area experience shorter dry spells that often last less than 1 mo (Fig. 9d).

Figure 9 also contains maps for comparison of how long 20 yr return period droughts are estimated to be by the climate models. Figure 9b (9e) shows the average 20 yr return period drought length of the 5 best climate models for the warm (cold) season and Fig. 9c (9f) the average of the 5 worst model estimations for the warm (cold) season. These comparisons show that the worst-performing models have a tendency to overestimate 20 yr return values in both seasons and across the majority of climate divisions.

4. DISCUSSION AND CONCLUSIONS

In general, the models perform better during the cold season, possibly due to the frontal-driven precipitation that dominates in the region during this season. During the cold season, the climate divisions with significant and high-value skill scores are clustered in more continental locations again, indicating that the models may be performing better in winter at locations subject to dominant frontal-driven precipitation rather than mixed processes. The models fail to significantly simulate the long extended dry periods occurring during the cold season in south Florida. It can be speculated that the climate of this region in winter is subject to differing physical mechanisms of precipitation. In winter, the dominant mechanism of precipitation is frontal activity from the southward movement of cold air. However, these fronts rarely reach South Florida and at the same time the temperatures are not high enough for convective precipitation. This results in extensive dry periods here during the winter. However, estimates of 20 yr return periods by the 5 best-performing models do simulate these periods to within ±5 d. These long dry periods in excess of 70 d, while occurring out of the growing season, may have a large impact on natural ecosystems and wildfires. In contrast, warm season precipitation is a result of convection, sea breeze and tropical cyclones, which tend to have a less predictable behavior and are spatially heterogeneous. This is reflected in the geographical spread of significant climate divisions depicted in Fig. 8a–e.

The findings of this study also emphasize the importance of ranking models based on performance. Through identifying the best- and worst-performing models, we have shown that there is large variability (>30 dry days for 20 yr returns) present between model simulations, and we note large overestimation of 20 yr returns by the worst-performing models across both seasons and almost all climate divisions. We suggest using skill scores to create a smaller yet better performing ensemble may be essential when investigating future impacts (see also, Perkins et al. 2013).

There are several limitations to the current work that center around definitions of seasons and dry spells. We have defined seasons from agricultural growing seasons that vary slightly in length, in start and end dates, and by crop type across the study region. In doing so, we have taken a fairly conservative and parsimonious approach by applying the longest growing season across the entire study region instead of varying the seasonal definition spatially. We believe this approach is preferable in that it makes for easier comparisons across the region. The use of 2 seasons in the analysis may also cut single consecutive dry spells in 2 if they straddle the start or end dates of the growing season, but as we have applied the same seasonal definitions across observations and models, this is likely to have little impact other than to reduce the occurrence of extreme long-duration events in all datasets. The simulation of timing of events within each season may be included in future analysis using a similar non-homogeneous Poisson process to the one applied by Keellings & Waylen (2014) to heatwaves. Another limitation lies in our definition of independence between dry spells, with 1 d of precipitation not necessarily being enough relief after a long dry spell if followed by numerous further days lacking in precipitation. The number of days of precipitation required to alleviate an extended dry period will ultimately vary based on the current precipitation deficit, the total precipitation occurring on days following a dry spell and indeed the lens of interest. We believe the 1 d separation applied here is adequate as we are purely focused on the ability of downscaled models to simulate dry periods.

Long periods of little to no precipitation have historically severely impacted the Southeast both environmentally and economically. In this study, climate models are used to simulate historical drought patterns in the Southeast. The downscaled models simulate the entire distribution of observed dry spells well, as shown by high PDF skill scores and significance tests. When focusing on longer or extreme dry periods, using tail skill scores and the stringent tail significance test, the models do not perform as well. However, selecting a smaller ensemble of the best-performing models improves simulation of extremes. The top 5 models provide good estimates of 20 yr return values in both the warm and cold seasons, and could hence be useful in an assessment of future drought risks in the Southeast.

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